Event-Triggered H_∞ Filtering for T–S Fuzzy-Model-Based Nonlinear Networked Systems With Multisensors Against DoS Attacks

Zhou Gu, *Member, IEEE*, Choon Ki Ahn, *Senior Member, IEEE*, Dong Yue, *Senior Member, IEEE*, and Xiangpeng Xie, *Member, IEEE*

***Abstract*—This article focuses on the problem of resilient H_∞ filtering for Takagi–Sugeno fuzzy-model-based nonlinear networked systems with multisensors. A weighted fusion approach is adopted before information from multisensors is transmitted over the network. A novel event-triggered mechanism is proposed, which allows us not only to reduce the data-releasing rate but also to prevent abnormal data being potentially transmitted over the network due to sensor measurement or other practical factors. The problem of denial-of-service (DoS) attacks, which often occurs in a communication network, is also considered, where the DoS attack model is based on an assumption that the periodic attack includes active periods and sleeping periods. By employing the idea of the switching model for filtering error systems to deal with DoS attacks, sufficient conditions are derived to guarantee that the filtering error system is exponentially stable. Simulation results are given to demonstrate the effectiveness of the theoretical analysis and design method.**

***Index Terms*—Denial-of-service (DoS) attacks, event-triggered mechanism (ETM), fuzzy filter design, multisensor fusion.**

I. INTRODUCTION

THE TAKAGI–SUGENO (T–S) fuzzy model with a series of IF-THEN fuzzy rules is commonly regarded as an ideal representation for modeling some types of nonlinear systems. To date, T–S fuzzy-model-based filter design has achieved many meaningful results [1]–[5]. For large-scale nonlinear systems, it is necessary to transfer information via a network, especially for systems with spatially distributed multisensors and some distributed systems [6]. Nonlinear systems with networked communication exist in a variety of environments, such as wireless sensor execution networks and underwater or underground control devices. Wen *et al.* [7] investigated the filtering problem for distributed systems by using quantized information that is transmitted over the sensor network. A filter design for distributed networked systems with sensor gain reduction and energy constraints was developed in [8]. The topology of a sensor network is known to play a crucial role in the nonlinear filter design from the perspective of security and precision [9]; however, this has not been fully studied yet, which is one of the motivations of this article.

High-frequency data transmission over a network not only requires more network communication and computation resources but also consumes more energy, which is fatal for resource-constrained networked systems, such as battery-based networked sensor systems. With the time-triggered mechanism (TTM), the worst-case scenarios need to be considered when choosing a fixed-releasing period, which may lead to great conservatism to control design [10]–[12]. For a system with the event-triggered mechanism (ETM), many sampling packets are not permitted to be released into the network. The measurement packet is released into the network only when the event-triggering condition (ETC) is violated, instead of being released at a fixed time with the TTM (see [13]–[17] and the references therein). Therefore, the ETM is a desirable alternative for reducing the network burden. A key issue in the ETM design is seeking reasonable conditions that can effectively reduce the data-releasing rate while retaining the control performance within a certain level. For example, in [13], a self-triggered condition that relies on continuous measurement was established; however, it is hard to implement for physical instruments, especially when the Zeno phenomenon occurs. To avoid the Zeno behavior, Heemels et al. [14] proposed an event-triggered scheme that combines the ideas of both periodic sampling and event-based releasing for discrete-time linear systems. Yue *et al.* [15] and Zhang *et al.* [18] took the network-induced delay into account in designing discrete ETMs for continuous-time networked control systems (NCSs), which is a natural problem in modeling NCSs. Note that the ETM threshold has a strong impact on the data-releasing rate. The fixed threshold, which has been commonly studied in the existing literature on the ETM, such as in [15]–[17], has some limitations for accommodating varying conditions. In fact, the

Manuscript received March 26, 2020; revised July 15, 2020 and September 8, 2020; accepted October 2, 2020. Date of publication November 5, 2020; date of current version June 16, 2022. This work was supported in part by the National Natural Science Foundation of China under Grant 62022044; in part by the Jiangsu Natural Science Foundation for Distinguished Young Scholars under Grant BK20190039; and in part by the National Research Foundation of Korea (NRF) grant funded by the Korea Government (Ministry of Science and ICT) under Grant NRF-2020R1A2C1005449. This article was recommended by Associate Editor X. M. Zhang. *(Corresponding authors: Zhou Gu; Choon Ki Ahn.)*

Zhou Gu is with the College of Mechanical and Electronic Engineering, Nanjing Forestry University, Nanjing 210037, China (e-mail: gzh1808@163.com).

Choon Ki Ahn is with the School of Electrical Engineering, Korea University, Seoul 136-701, South Korea (e-mail: hironaka@korea.ac.kr).

Dong Yue and Xiangpeng Xie are with the Institute of Advanced Technology, Nanjing University of Posts and Telecommunications, Nanjing 210023, China (e-mail: medongy@vip.163.com; xiexiangpeng1953@163.com).

Color versions of one or more figures in this article are available at https://doi.org/10.1109/TCYB.2020.3030028.

Digital Object Identifier 10.1109/TCYB.2020.3030028

desired ETM can result in not only a low data-releasing rate but also in excellent control performance. For example, the controller/the filter requires more data to achieve higher quality control in the case of NCSs with strong interference for a certain period of time. With this motivation, a time-varying function with respect to the state was used to replace the fixed threshold in [19]. Gu *et al.* [20] and Zhang *et al.* [21] designed an adaptive threshold that can dynamically adjust with the external disturbance for continuous-time and discrete-time fuzzy systems, respectively. In [22], a dynamic ETM was developed to obtain better resource efficiency. However, few studies focus on this issue, which is another main motivation of our current investigation.

Besides the issue of limited network bandwidth, another issue of NCSs that needs to be seriously considered is cyber-attacks. Tampering and intercepting the data that need to be transmitted over the network are the most common types, through which the attackers can destabilize or even destroy a target system [23]. For these reasons, a security controller/filter based on network communication has attracted increasing research interest. In [24], the deception attack was assumed to satisfy a quasi-Lipschitz condition that depends on the state of the system. Ding *et al.* [25] investigated the problem of observer-based control design for multiagent systems with error data injection into the control input. The denial-of-service (DoS) attack is another typical type of cyber-attack [26], [27]. The main purpose of this type of attack is to jam the channels of communication networks. The filter/controller in this situation cannot access the required data, thereby deteriorating the performance. In [28], a DoS attack model was established for a continuous-time linear NCS under the assumption that the attack period is known. So far, few works of literature have focused on the problem of multisensor-based nonlinear filtering systems subject to DoS attacks.

Motivated by the above discussions, in this article, we are interested in investigating the event-triggered fuzzy filter for nonlinear systems with multisensors against DoS attacks. The main contributions of this article are summarized as follows.

1) A new model of distributed ETMs is established, in which some abrupt data that are unnecessary to the system are prevented from being released into the network. In addition, when the system is subject to external interference, the filter can acquire more data than in other periods to achieve better performance.
2) A weighted fusion method is used for multisensors to enhance the reliability of filtering systems before the decision of ETMs.
3) DoS attacks are considered for the secure filter design of T–S fuzzy-model-based networked systems. In modeling the DoS attack, the period of the DoS attack includes an active period and a sleeping period, where the sleeping period is assumed to be variable, while the entire period of the DoS attack is fixed.

The remainder of this article is organized as follows. The model description of fuzzy systems with multisensors and the model of considered problems are provided in Section II. In Section III, a secure filter is designed to ensure that the T–S fuzzy model-based error filtering systems subject to DoS attacks is exponentially stable. In Section IV, an example is given to demonstrate the advantages of the proposed approach. Finally, we conclude this article in Section V.

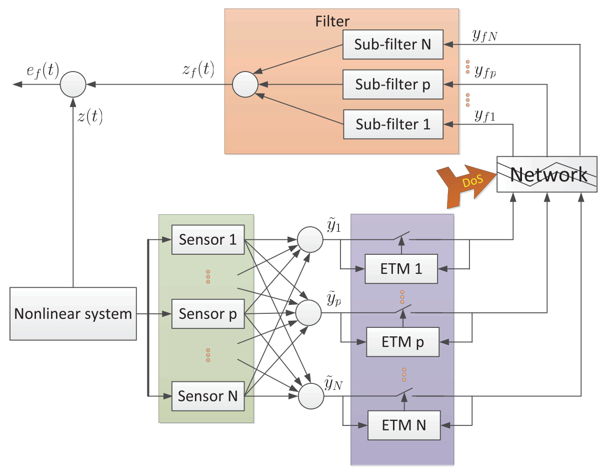


Fig. 1. Framework of nonlinear networked filtering systems.

Notation: The notations presented in this study are standard. Individually, $\mathrm{diag}_N\{A\}$ denotes $\mathrm{diag}\{\underbrace{A,\ldots,A}_{N}\}$, $\mathrm{diag}_N^p\{A\}$ denotes $\mathrm{diag}\{\underbrace{0,\ldots,0}_{p-1},A,\underbrace{0,\ldots,0}_{N-p}\}$, and $\mathrm{diag}_{p=1}^N\{A_p\}$ denotes $\mathrm{diag}\{A_1,\ldots,A_N\}$. Similarly, $\mathrm{col}_N\{x\}$ and $\mathrm{col}_N^p\{x\}$ denote $[\underbrace{x^T,\ldots,x^T}_{N}]^T$ and $[\underbrace{0,\ldots,0}_{p-1},x^T,\underbrace{0,\ldots,0}_{N-p}]^T$, respectively; $\mathrm{col}\{x_1,x_2,\ldots,x_N\}$ is denoted by $\mathrm{col}_{p=1}^N\{x_p\}$; $\mathrm{Sym}\{X\}$ represents $X+X^T$, and $\{y\}_i$ represents the ith element of the vector y.

II. Problem Statement

As shown in Fig. 1, data fusion is performed before the output signal of the nonlinear system is released into the network. To alleviate the burden of the network bandwidth, the ETM is introduced. The main task of this research is to design a network-based secure fuzzy filter and an ETM in response to DoS attacks. For description convenience, we first introduce the following symbols to describe the relationship among the multisensors: the set of sensor nodes is denoted by $\mathcal{V}$ ($\triangleq \{1,2,\ldots,N\}$); and $\mathcal{E}$ belonging to $\mathcal{V}\times\mathcal{V}$ represents the edge set of paired sensor nodes; and $\mathcal{N}_p$ indicates the set of the pth sensor node that connects to the other sensor nodes (i.e., $\mathcal{N}_p \triangleq \{q|(p,q)\in\mathcal{E}\}$). $\mathcal{W}$ ($\triangleq [w_{pq}]\in\mathbb{R}^{N\times N}$) means the weighted adjacency matrix, where p,q denotes different sensor nodes.

Fig. 1 shows the framework of the filtering for networked nonlinear systems with multisensors. The nonlinear system that needs to be estimated can be represented by the following T–S fuzzy model.

Plant Rule i: If $r_1(t)$ is Γ_{i1}, ..., and $r_g(t)$ is Γ_{ig}, then

$$\begin{cases}\dot{x}(t)=A_ix(t)+B_i\omega(t)\\ z(t)=E_ix(t)\\ y_p(t)=C_{pi}x(t)\end{cases}\tag{1}$$

where $\Gamma_{i1}, \Gamma_{i2}, \ldots, \Gamma_{ig}$ are the fuzzy sets, $i \in \mathscr{I} \triangleq \{1, 2, \ldots, w\}$; $r_1(t)$, $r_2(t)$, $\ldots$, $r_g(t)$ are the premise variables; $x(t) \in \mathbb{R}^n$ is the state vector, $y_p(t) \in \mathbb{R}^{m_1}$ and $z(t) \in \mathbb{R}^{m_2}$ are the output measured by the pth ($p \in \mathcal{V}$) sensor and the output to be estimated, respectively; and $\omega(t) \in \mathbb{R}^{m_3}$ denotes the external disturbance that belongs to $l_2[0, \infty)$. A_i, B_i, C_{pi}, and E_i are known constant matrices with appropriate dimensions.

To enhance the reliability, the precision, and the filter cost, a weighted fusion approach for multisensors is applied here. The input of the pth filter in this study is not only from the pth sensor but also from the others among multisensors, which is given by

$$\tilde{y}_p(t) = \sum_{q \in \mathcal{N}_p} w_{pq} y_q(t). \tag{2}$$

Remark 1: By introducing the weighted fusion approach here, the filter precision can be improved, since the filter input fuses the information from multiple channels. Moreover, this structure with multisensors is more reliable for data transmission. Supposing that the ith sensor fails to provide the plant output, we can use the data coming from other sensor nodes to partially represent the ith information. In addition, one can use several low-cost sensors to replace expensive precision instruments, and then use a reasonable algorithm to gain the expected results.

Similar to [29] and [30], we can obtain the following concise dynamics to represent the system (1):

$$\begin{cases} \dot{x}(t) = \sum_{i=1}^{w} \sigma_i(r(t))[A_i x(t) + B_i \omega(t)] \\ z(t) = \sum_{i=1}^{w} \sigma_i(r(t)) E_i x(t) \\ \tilde{y}_p(t) = \sum_{i=1}^{w} \sum_{q \in \mathcal{N}_p} \sigma_i(r(t)) w_{pq} C_{qi} x(t) \end{cases} \tag{3}$$

where $\sigma_i(r(t)) = (\varsigma_i(r(t))/\sum_{i=1}^{w} \varsigma_i(r(t))) \geq 0$, $\varsigma_i(r(t)) = \Pi_{s=1}^{g} \Gamma_{is}(r_s(t))$ with $r(t) = [r_1(t), r_2(t), \ldots, r_g(t)]^T$ for $i \in \mathscr{I}$, $\Gamma_{is}(r_s(t))$ is the grade of the membership function Γ_{is}. Obviously, $\sum_{i=1}^{w} \sigma_i(r(t)) = 1$.

Since the premise variable $r(t)$ in (3) is asynchronous to the one after being transmitted over the network, we denote it as $\hat{r}(t)$. Considering the problem of asynchronization, we construct the jth fuzzy filter shown in Fig. 1 as follows.

Plant Rule j: If $\hat{r}_1(t)$ is Γ_{j1},..., $\hat{r}_g(t)$ is Γ_{jg}, then

$$\begin{cases} \dot{x}_{fp}(t) = A_{fpj} x_{fp}(t) + B_{fpj} y_{fp}(t) \\ z_{fp}(t) = C_{fpj} x_{fp}(t) \end{cases} \tag{4}$$

where $x_{fp}(t) \in \mathbb{R}^n$ and $z_{fp}(t) \in \mathbb{R}^p$ are the state vector and the output vector of the pth filter, respectively, and A_{fpj}, B_{fpj}, and C_{fpj} are the parameters of the pth filter that need to be designed. The DoS attack is considered when the information is transmitted through the network. Therefore, $y_{fp}(t)$ in (4) is the real input of the pth filter, which differs from $\tilde{y}_p(t)$ in (3).

The compact presentation of the fuzzy filter (4) is then followed by:

$$\begin{cases} \dot{x}_{fp}(t) = \sum_{j=1}^{w} \sigma_j(\hat{r}(t))[A_{fpj} x_{fp}(t) + B_{fpj} y_{fp}(t)] \\ z_f(t) = \frac{1}{N} \sum_{p=1}^{N} \sum_{j=1}^{w} \sigma_j(\hat{r}(t)) C_{fpj} x_{fp}(t). \end{cases} \tag{5}$$

Remark 2: In (5), the output $z_f(t)$ is the estimation of the output $z(t)$. Here, we design a centralized filter by taking an average for p outputs of the filter as the final estimation. Therefore, the viewpoint of this study differs from that regarding the distributed filter investigated in [9].

For simplicity, $\sigma_i(r(t))$ and $\sigma_j(\hat{r}(t))$ are abbreviated as σ_i^r and $\sigma_j^{\hat{r}}$ next. Similar to [31], here, we assume that $\sigma_j^{\hat{r}} - \kappa_j \sigma_j^r \geq 0$ $(0 < \kappa_j \leq 1)$ in this study.

From Fig. 1, one can see that the following three factors that will still affect the real input of the filter after the fusion described in (2): 1) the distributed ETM; 2) the DoS attack; and 3) the channel fading.

For the first case, we introduce distributed ETMs to cater for the structure of multisensors. Whether the current data from each sampler is "necessary" to the subfilter is determined by its corresponding ETM. The ETM in most available literature, such as in [32], has the following format:

$$\tilde{e}_p^T(t) \Omega_p \tilde{e}_p(t) \leq \sigma \tilde{y}_p^T\big(t_k^p h\big) \Omega_p \tilde{y}_p\big(t_k^p h\big) \tag{6}$$

where $\tilde{e}_p(t) \triangleq \tilde{y}_p(t_k^p h + lh) - \tilde{y}_p(t_k^p h)$; h is the sampling period; $\{t_k^p h\}_{t_k^p=0,1,2,\ldots,}$ is the sequence of releasing instants; $\{t_k^p h + lh\}_{t_k^p=0,1,2,\ldots,}$ is the sequence of sampling instants with $l = 1, 2, 3, \ldots, \bar{l}$. $\Omega_p > 0$ are weighting matrices to be designed.

It has been proved that this type of ETM can reduce the network burden immensely; however, there is still much room for improvement regarding this issue, warranting a further study.

From (6), one knows that abrupt data (sometimes completely incorrect data) are more likely to violate the condition than those with normal variation. These data are mistakenly regarded as necessary data and released into the network. To avoid this erroneous event, we need to redefine the error $\tilde{e}_p(t)$ in (6). Before performing this, we first construct an artificial output as

$$\tilde{y}_p\big(t_k^p h + \Delta h\big) = \mu\big[\tilde{y}_p\big(t_k^p h + lh\big) - \tilde{y}_p\big(t_k^p h\big)\big] + \tilde{y}_p\big(t_k^p h\big) \tag{7}$$

where μ is an adjustment factor that satisfies $\mu \in (0, 1]$, $0 < \Delta h < lh$.

Obviously, using $\tilde{y}_p(t_k^p h + \Delta h)$ to replace the current sampling data $\tilde{y}_p(t_k^p h + lh)$ when calculating the error $\tilde{e}_p(t)$ will mitigate this phenomenon. Then, the new error becomes

$$e_k^p(t) = \tilde{y}_p\big(t_k^p h\big) - \tilde{y}_p\big(t_k^p h + \Delta h\big). \tag{8}$$

Remark 3: In (7), if one sets $\mu = 1$, the error in (8) reduces to the conventional ETM in (6). For the case where $0 < \mu \leq 1$, the result of $\{\tilde{y}_p(t_k^p h + \Delta h)\}_i$ will be a certain value between $\{\tilde{y}_p(t_k^p h)\}_i$ and $\{\tilde{y}_p(t_k^p h + lh)\}_i$ for $i = 1, 2, \ldots, m$. In particular, if μ equals to 0.5, $\{\tilde{y}_p(t_k^p h + \Delta h)\}_i$ turns to be an average value between the current sampling data and the latest released data. Therefore, using the artificial output in (7) can mitigate the occurrence of erroneous events.

Furthermore, the system is expected to have a higher data-releasing rate during the period of the disturbance than other periods, thereby improving control performance. However, the traditional ETM cannot meet this requirement. To compensate for this defect, a further improvement of the ETM is made

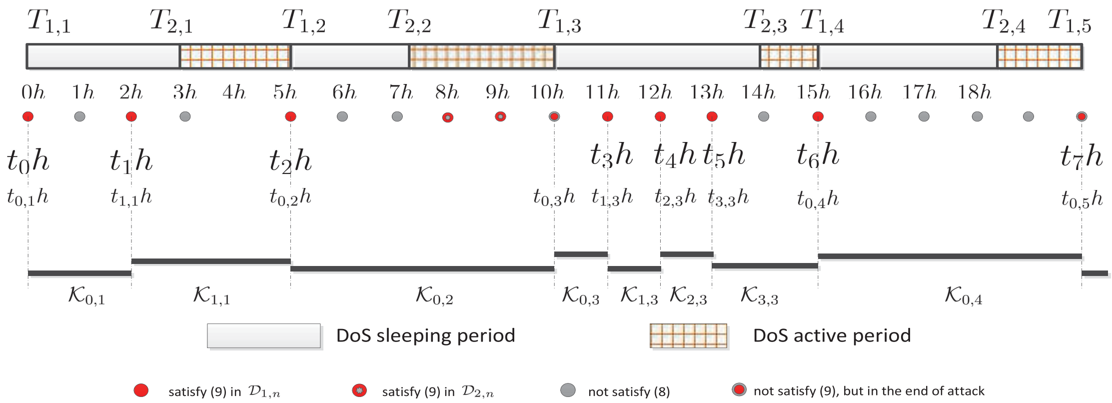


Fig. 2. Example of the sequence of DoS attacks and ETM.

as follows:

$$e_k^{p^T}(t)\Omega_p e_k^p(t) \le \ell_1 \tilde{y}_p^T(t_k^p h)\Omega_p \tilde{y}_p(t_k^p h) + \frac{\ell_2}{2}\left[\tilde{y}_p^T(t_k^p h)\Omega_p e_k^p(t) + e_k^{p^T}(t)\Omega_p \tilde{y}_p(t_k^p h)\right] \tag{9}$$

where $\ell_1 > 0$ and $\ell_2 > 0$ are given scalars.

The next releasing instant of the pth ETM can be expressed by

$$t_{k+1}^p h = t_k^p h + (\bar{l}+1)h \tag{10}$$

where $\bar{l} = \max\ \{l\}$ s.t. (9).

Next, we consider the case of a DoS attack, which is one of a typical cyber-attack. Networked filtering systems are vulnerable to cyber-attacks launched by malicious agents. The consequence of this type of attack is that some released packets cannot reach the terminal of the communication network. The signal is set to be zero during attack-active periods.

As is shown in Fig. 2, the nth DoS attack period $\mathfrak{D}_n$ is composed of the DoS sleeping period $\mathfrak{D}_{1,n}$ and the DoS active period $\mathfrak{D}_{2,n}$. Denote $T_{1,n}$ and $T_{2,n}$ as the start instants of the nth DoS sleeping period and DoS active period, respectively. Then, the nth sleeping period of the DoS attack is $T_s^n = T_{2,n} - T_{1,n}$ and the nth active period of the DoS attack is $T_a^n = T_{1,n+1} - T_{2,n}$. It follows that $\mathfrak{D}_n = \mathfrak{D}_{1,n} \cup \mathfrak{D}_{2,n} = [T_{1,n}, T_{1,n+1})$ and the DoS attack period is $T_{\text{dos}} = T_s^n + T_a^n$. Suppose that T_{dos} is a fixed constant while the sleeping periods T_s and T_a are varying. It is clear that $T_s^n \le T_{\text{dos}}$ and $T_a^n \le T_{\text{dos}}$. Then, the intervals of the DoS sleeping period and the active period can be represented by $\mathfrak{D}_{1,n} = [T_{1,n}, T_{1,n} + T_s^n)$ and $\mathfrak{D}_{2,n} = [T_{1,n} + T_s^n, T_{1,n+1})$, respectively. To guarantee the reliability of the control system, we make a reasonable assumption that the packet at the end of each attack period ($T_{1,n}$) should be released into the network regardless of whether it satisfies the ETC in (9), such as the packets at instant $5h$, $10h$, $15h, \ldots,$ in Fig. 2, where the packet at instant $10h$ does not satisfy the ETC (9), but it is necessary for improving the filter performance.

For an explicit description, we denote the sequence that satisfies ETC (9) in the DoS sleeping period $\mathfrak{D}_{1,n}$ as $\{t_k^p h\}$. The packet in the attacking period $\mathfrak{D}_{2,n}$ cannot reach the filter side even if it satisfies the ETC, such as the packets at instant $8h, 9h, \ldots,$ in Fig. 2.

From the above discussion, it can be determined that the sampling packet at instant $t_{v,n}^p h$ in $\mathfrak{D}_n$ can be successfully acquired by the subfilter, which can be expressed as

$$\{t_{v,n}^p h\} = \{T_{1,n}\} \cup \{t_k^p h\} \tag{11}$$

where v $(= 0, 1, 2, \ldots, \bar{v})$ denotes the vth packet that needs to be transmitted in the DoS sleeping period $\mathfrak{D}_{1,n}$. Consequently, $t_{v,n}^p h < T_{1,n} + T_s^n = (n-1)T_{\text{dos}} + T_s^n$.

Considering the DoS attack and the ETM, the filter input can be expressed as

$$\hat{y}_{fp}(t) = \begin{cases} \tilde{y}_p(t_{v,n}^p h), & t \in \mathcal{K}_{v,n} \cap \mathfrak{D}_{1,n} \\ 0, & t \in \mathfrak{D}_{2,n} \end{cases} \tag{12}$$

where $\mathcal{K}_{v,n} \triangleq [t_{v,n}^p h, t_{v+1,n}^p h)$.

Since the packet at instant $T_{1,n}$ should be transmitted, item $e_k^p(t)$ in (9) needs to be modified to

$$e_{v,n}^p(t) = \tilde{y}_p(t_{v,n}^p h) - \tilde{y}_p(t_{v,n}^p h + \Delta h) \tag{13}$$

where $\tilde{y}_p(t_{v,n}^p h + \Delta h) = \mu[\tilde{y}_p(t_{v,n}^p h + lh) - \tilde{y}_p(t_{v,n}^p h)] + \tilde{y}_p(t_{v,n}^p h)$ with $l = 1, 2, \ldots, \bar{l}$, $\bar{l} = \min\{t_{v+1,n}^p, t_{0,n+1}^p\} - t_{v,n}^p - 1$.

Define $\mathscr{I}_{v,n,l} = [t_{v,n}^p h + lh, t_{v,n}^p h + (l+1)h)$ for $l = 0, 1, 2, \ldots, \bar{l}$. Using a similar modeling method of sampling control to that in [33], we define $d_{v,n,l}^p(t) = t - t_{v,n}^p h - lh$.

Remark 4: From the above discussion, one can know that $t_{v,n}^p h + (\bar{l}+1)h = \min\{t_{v+1,n}^p h, t_{0,n+1}^p h\}$. In addition, from $\mathscr{I}_{v,n,l}$, one has $d_{v,n,l}^p(t) \in [0, h)$.

Based on the definition of $d_{v,n,l}^p(t)$, by combining (3) and (7), the filter input can be rewritten as

$$y_{fp}(t) = \sum_{i=1}^{w} \sigma_i^r\big(r(t_{v,n}^p h)\big)\lambda_p \times \left[\frac{1}{\mu}e_{v,n}^p(t) + \sum_{q\in\mathcal{N}_p} w_{pq}C_{qi}x\big(t - d_{v,n,l}^p(t)\big)\right] \tag{14}$$

where λ_p is a channel-fading coefficient that takes a value over the interval $[0, 1]$.

Remark 5: In (14), the problem of channel fading, the third case mentioned above, is considered. Channel fading in network communication, especially in a wireless network, is a common phenomenon (see [35]–[37]). In (14), if one lets $\lambda_p = 1$, this means that the pth communication channel does not experience the signal loss, whereas λ_p tending to be zero implies that the pth communication channel has serious communication problems that will result in poor filtering performance.

From (12), one can determine that the filtering dynamic has different inputs due to DoS attacks, which makes the filtering system more complicated. To ensure a compact format, we define $\bar{x}(t) = \mathrm{col}_N\{x(t)\}$, $\bar{x}_f(t) = \mathrm{col}_{p=1}^N\{x_{fp}(t)\}$, $\varphi(t) = \mathrm{col}\{\bar{x}(t), \bar{x}_f(t)\}$, $e_f(t) = z(t) - z_f(t)$, $\bar{e}_{v,n}^p(t) = \mathrm{col}_N^p\{e_{v,n}^p(t)\}$, $\bar{A}_i = \mathrm{diag}_N\{A_i\}$, $\bar{B}_i = \mathrm{col}_N\{B_i\}$, $\bar{C}_i = \mathrm{diag}_{p=1}^N\{C_{pi}\}$, $\bar{A}_{fmj} = \mathrm{diag}_{p=1}^N\{A_{fmpj}\}$, $\bar{B}_{fpj} = \mathrm{diag}_N^p\{B_{fpj}\}$, $\bar{C}_{fmj} = \mathrm{diag}_{p=1}^N\{C_{fmpj}\}$, $\hat{C}_i = \{\mathrm{col}_{p=1}^N\{C_{pi}\}, \underbrace{0, \ldots, 0}_{N-1}\}$, and $\bar{E}_i = \mathrm{diag}_N\{E_i\}$.

Then, the error filtering system for $t \in \mathscr{I}_{v,n,l}$ can be remodeled as the following switched fuzzy system with $m \in \{1, 2\}$:

$$\begin{cases} \dot{\varphi}(t) = \sum_{i=1}^w \sum_{j=1}^w \sum_{p=1}^N \sigma_i^r \sigma_j^{\hat{r}} \\ \qquad \times \Big[\tilde{A}_{mij}\varphi(t) + \tilde{B}_i\omega(t) \\ \qquad + \lambda_p\Big(\tilde{D}_{mpij}\bar{x}\Big(t - d_{v,n,l}^p(t)\Big) + \tilde{C}_{mpij}\bar{e}_{v,n}^p(t)\Big)\Big] \\ e_f(t) = \sum_{i=1}^w \sum_{j=1}^w \sigma_i^r \sigma_j^{\hat{r}} \tilde{E}_{mij}\varphi(t) \end{cases} \tag{15}$$

where

$$\tilde{A}_{mij} = \begin{bmatrix} \bar{A}_i & 0 \\ 0 & \bar{A}_{fmj} \end{bmatrix}, \tilde{B}_i = \begin{bmatrix} \bar{B}_i \\ 0 \end{bmatrix}, \tilde{C}_{1pj} = \begin{bmatrix} 0 \\ \frac{1}{\mu}\bar{B}_{fpj} \end{bmatrix}$$
$$\tilde{D}_{1pij} = \begin{bmatrix} 0 \\ \bar{B}_{fpj}(\mathcal{W} \otimes I)\hat{C}_i \end{bmatrix}, \tilde{E}_{mij} = \frac{1}{N}\begin{bmatrix} \bar{E}_i & -\bar{C}_{fmj} \end{bmatrix}$$
$$H = \begin{bmatrix} I & 0 \end{bmatrix}, \tilde{C}_{2pj} = \tilde{D}_{2pij} = 0.$$

In (15), for $m = 1$, it denotes the filtering error dynamic during the DoS sleeping period (i.e., $t \in \mathfrak{D}_{1,n}$). For $m = 2$, it represents the filtering error dynamic for $t \in \mathfrak{D}_{2,n}$; that is, the DoS attack is in the active period.

The objective of this research is to design the secure filter such that the switched filtering error system (15) under DoS attacks is exponentially stable with the H_∞ attenuation level γ based on the distributed ETMs.

III. Main Results

In Section II, networked nonlinear filtering systems considering DoS attacks and channel fading are modeled as a switched system. In this section, we will derive sufficient conditions in Theorem 1 to guarantee that the filtering error system (15) is exponentially stable. The gains of the filter will be given in Theorem 2.

Theorem 1: For prescribed positive scalars κ_i, β_1, β_2, $\varrho_0, \varrho_2, \rho, \ell_1, \ell_2$, and γ, by using the ETM in (10), the filtering error system (15) considering DoS attacks with the maximum of the DoS duration time $T_a^{\max} = ([\beta_1 T - \ln\sqrt{\varrho_0\varrho_2}]/[(\beta_1 + \beta_2)]) - h$ is exponentially stable, if there exist matrices $P_m > 0, \Omega_p > 0, Q_m > 0, L_{mp} > 0, U_{mp} > 0$, and Ξ_i with appropriate dimensions such that the following matrix inequalities hold:

$$\check{\Phi}^{mij} < 0 \tag{16}$$
$$\kappa_j\check{\Phi}^{mij} + \kappa_i\check{\Phi}^{mji} + \Xi_i + \Xi_j < 0, \quad (i \le j) \tag{17}$$
$$P_{3-m} \le \varrho_m P_m \tag{18}$$
$$Q_m \le \varrho_{4-2m}Q_{3-m} \tag{19}$$
$$L_{mp} \le \varrho_{4-2m}L_{(3-m)p} \tag{20}$$
$$\begin{bmatrix} L_{mp} & * \\ U_{mp}^T & L_{mp} \end{bmatrix} \ge 0 \tag{21}$$

with $m = 1, 2;\ i, j \in \mathscr{I}, p \in \mathcal{V}$, where

$$\check{\Phi}^{mij} = \begin{bmatrix} \Phi_{11}^{mij} - \Xi_i & * \\ \Phi_{21}^{mij} & \Phi_{22}^m \end{bmatrix}$$
$$\Phi_{11}^{1ij} = \begin{bmatrix} \Psi_{11ij}^1 & * & * & * & * \\ \Psi_{21}^1 & \Psi_{22}^1 & * & * & * \\ \tilde{B}_i^T P_1 & 0 & -\gamma^2 I & * & * \\ \Psi_{41ij}^1 & \Psi_{42}^1 & 0 & \Psi_{44i}^1 & * \\ \Psi_{51j}^1 & 0 & 0 & \Psi_{54i}^1 & \Psi_{55}^1 \end{bmatrix}$$
$$\varpi_m = e^{-2\beta_m(2-m)h}, \varrho_1 = \varrho_0 e^{2(\beta_1+\beta_2)h}$$
$$\Phi_{11}^{2ij} = \begin{bmatrix} \Psi_{11ij}^2 & * & * & * \\ \Psi_{21}^2 & \Psi_{22}^2 & * & * \\ \tilde{B}_i^T P_2 & 0 & -\gamma^2 I & * \\ \Psi_{41ij}^2 & \Psi_{42}^2 & 0 & \Psi_{44i}^2 \end{bmatrix}$$
$$\Psi_{11ij}^m = \mathrm{Sym}\Big\{P_m\tilde{A}_{mij} + (-1)^{m+1}\beta_m P_m\Big\} + H^T Q_m H - \frac{\varpi_m}{h}H^T\sum_{p=1}^N L_{mp}H, \Psi_{21}^m = \frac{\varpi_m}{h}\sum_{p=1}^N U_{mp}H$$
$$\Psi_{22}^m = -\varpi_m Q_m - \frac{\varpi_m}{h}\sum_{p=1}^N L_{mp}$$
$$\Psi_{41ij}^m = \mathrm{col}_N\Big\{\mathcal{L}_{mp}^4\Big\}, \Psi_{44i}^m = \mathrm{diag}_N\Big\{\mathcal{T}_{mp}^4\Big\}$$
$$\mathcal{L}_{mp}^4 = (2-m)\lambda_p\tilde{D}_{1pij}^T P_m + \frac{\varpi_m}{h}\Big(L^T{}_{mp} - U_{mp}^T\Big)H$$
$$\mathcal{T}_{mp}^4 = \frac{\varpi_m}{h}\big(-2L_{mp} + \mathrm{Sym}\{U_{mp}\}\big) + (2-m)\Theta_1^p$$
$$\Psi_{42}^m = \mathrm{col}_N\Big\{\mathcal{S}_{mp}^4\Big\}, \mathcal{S}_{mp}^4 = \frac{\varpi_m}{h}(L_{mp} - U_{mp})$$
$$\Psi_{51j}^1 = \mathrm{col}_N\Big\{\lambda_p\tilde{C}_{1pj}^T P_1\Big\}, \mathcal{I}_p = \mathrm{diag}_N^i\{I\}$$
$$\Theta_1^p = \varepsilon_2^2\hat{C}_i^T(\mathcal{W} \otimes I)^T\mathcal{I}_p^T\Omega_p\mathcal{I}_p(\mathcal{W} \otimes I)\hat{C}_i$$
$$\Psi_{54i}^1 = \mathrm{diag}_N\Big\{\varepsilon_2\Big(\mu^{-1}\varepsilon_2 + \varepsilon_3\Big)\Omega_p\mathcal{I}_p(\mathcal{W} \otimes I)\hat{C}_i\Big\}$$
$$\Psi_{55}^1 = \mathrm{diag}_N\Big\{\Big(\Big(\mu^{-1}\varepsilon_2 + \varepsilon_3\Big)^2 - \varepsilon_1\Big)\Omega_p\Big\}$$
$$\Phi_{21}^{mij} = \begin{bmatrix} \Phi_{1m}^{ij\ T} & \Phi_{2m}^{ij\ T} \end{bmatrix}^T, \Phi_{21}^{ij} = \begin{bmatrix} \tilde{E}_{mij} & 0 & 0 & 0 & 0 \end{bmatrix}$$
$$\Phi_{22}^{ij} = \begin{bmatrix} \tilde{E}_{mij} & 0 & 0 & 0 \end{bmatrix}, \Phi_{22}^m = \mathrm{diag}\Big\{-L_{mp}^{-1}, -I\Big\}$$
$$\Phi_{11}^{ij} = \sqrt{h}H\begin{bmatrix} \tilde{\mathcal{A}}_{mij} & 0 & \tilde{\mathcal{B}}_i & \tilde{\mathcal{D}}_{1pij} & \tilde{\mathcal{C}}_{1pj} \end{bmatrix}$$
$$\Phi_{12}^{ij} = \sqrt{h}H\begin{bmatrix} \tilde{\mathcal{A}}_{mij} & 0 & \tilde{\mathcal{B}}_i & 0 \end{bmatrix}$$
$$\tilde{\mathcal{A}}_{mij} = \mathrm{col}_N\Big\{\tilde{A}_{mij}\Big\}, \tilde{\mathcal{B}}_i = \mathrm{col}_N\Big\{\tilde{B}_i\Big\}$$
$$\tilde{\mathcal{D}}_{1pij} = \mathrm{col}_N\Big\{\lambda_p\tilde{D}_{1pij}\Big\}, \tilde{\mathcal{C}}_{1pj} = \mathrm{col}_N\Big\{\lambda_p\tilde{C}_{1pj}\Big\}$$

$$\varepsilon_1 = 4\ell_1 + \ell_2^2, \varepsilon_2 = 2\ell_1, \varepsilon_3 = 0.5\varepsilon_2 + \sqrt{\varepsilon_1 - 2\varepsilon_2}.$$

Proof: For description convenience, we define

$$\xi_1(t) = \left[\varphi^T(t),\ \varphi^T(t-h)H^T,\ \omega^T(t),\ \psi_1^T(t),\ \psi_2^T(t)\right]^T$$
$$\xi_2(t) = \left[\varphi^T(t),\ \varphi^T(t-h)H^T,\ \omega^T(t), \psi_1^T(t)\right]^T$$
$$\mathfrak{e}_m(t,s) = e^{2(-1)^m \beta_m (t-s)}$$

where $\psi_1(t) = \text{col}_N\{H\varphi(t - d_{v,n,l}^p(t))\}$ and $\psi_2(t) = \text{col}_N\{H\tilde{e}_{v,n}^p(t)\}$.

For the filtering error system (15) in the DoS sleeping period with $m = 1$ and the DoS active period with $m = 2$, we construct the following Lyapunov–Krasovskii functional candidate:

$$V(t) = V_m(t) \tag{22}$$

for $t \in \mathfrak{D}_{m,n}$ with $m \in \{1, 2\}$, where

$$V_m(t) = \varphi^T(t)P_m\varphi(t) + \int_{t-h}^{t} \mathfrak{e}_m(t,s)\varphi^T(s)H^T Q_m H\varphi(s)ds + \int_{-h}^{0}\int_{t+v}^{t}\sum_{p=1}^{N}\mathfrak{e}_m(t,s)\dot{\varphi}^T(s)H^T L_{mp}H\dot{\varphi}(s)dsdv.$$

First, we consider the case of $m = 1$.

By taking the derivative of $V_1(t)$ along the filtering error system (15), it follows that:

$$\begin{aligned}\dot{V}_1(t) \le & -2\beta_1 V_1(t) + 2\varphi^T(t)P_1\dot{\varphi}(t)\\ & + \varphi^T(t)\left[2\beta_1 P_1 + H^T Q_1 H\right]\varphi(t)\\ & + \sum_{p=1}^{N} h\dot{\varphi}^T(t)H^T L_{1p}H\dot{\varphi}(t)\\ & - e^{-2\beta_1 h}\varphi^T(t-h)H^T Q_1 H\varphi(t-h)\\ & - e^{-2\beta_1 h}\int_{t-h}^{t}\sum_{p=1}^{N}\dot{\varphi}^T(s)H^T L_{1p}H\dot{\varphi}(s)ds.\end{aligned} \tag{23}$$

By applying Jensen's inequality lemma, we can obtain

$$-h\int_{t-h}^{t}\dot{\varphi}^T(s)H^T L_{1p}H\dot{\varphi}(s)ds \le \zeta^T(t)\mho\zeta(t) \tag{24}$$

where $\zeta(t) = \text{col}\{\varphi(t),\ H\varphi(t - d_{v,n,l}^p(t)),\ H\varphi(t-h)\}$ and

$$\mho = \begin{bmatrix} -H^T L_{1p} H & * & * \\ \left(L_{1p}^T - U_{1p}^T\right)H & -2L_{1p}^T + U_{1p} + U_{1p}^T & * \\ U_{1p}^T H & L_{1p}^T - U_{1p}^T & -L_{1p}\end{bmatrix}.$$

By defining $\varepsilon_1 = 4\ell_1 + \ell_2^2$, $\varepsilon_2 = 2\ell_1$, and $\varepsilon_3 = 0.5\varepsilon_2 + \sqrt{\varepsilon_1 - 2\varepsilon_2}$, one can easily find that the ETC (9) is equivalent to

$$\begin{aligned}&\varepsilon_1 e_{k,n}^{p\ T}(t)\Omega_p e_{v,n}^p(t)\\ &\le \left[\varepsilon_2\tilde{y}\left(t_{v,n}^p h\right) + \varepsilon_3 e_{v,n}^p(t)\right]^T\Omega_p\left[\varepsilon_2\tilde{y}\left(t_{v,n}^p h\right) + \varepsilon_3 e_{v,n}^p(t)\right].\end{aligned} \tag{25}$$

By combining (23)–(25), it follows that:

$$\begin{aligned}&\dot{V}_1(t) + 2\beta_1 V_1(t) - \gamma^2\omega^T(t)\omega(t) + e_f^T(t)e_f(t)\\ &\le \sum_{i=1}^{w}\sum_{j=1}^{w}\sigma_i^r\sigma_j^{\hat{r}}\xi_1^T(t)\tilde{\Phi}^{1ij}\xi_1(t)\end{aligned} \tag{26}$$

where $\tilde{\Phi}^{1ij} = \Phi_{11}^{1ij} + \Phi_{21}^{1ij^T}\Phi_{22}^{1\ -1}\Phi_{21}^{1ij}$.

Due to

$$\begin{aligned}&\sum_{i=1}^{w}\sum_{j=1}^{w}\sigma_i^r\left(\sigma_j^r - \sigma_j^{\hat{r}}\right)\xi_1^T(t)\Xi_i\xi_1(t)\\ &= \sum_{i=1}^{w}\sigma_i^r\left(\sum_{j=1}^{w}\sigma_j^r - \sum_{j=1}^{w}\sigma_j^{\hat{r}}\right)\xi_1^T(t)\Xi_i\xi_1(t) = 0\end{aligned} \tag{27}$$

we know that

$$\begin{aligned}&\sum_{i=1}^{w}\sum_{j=1}^{w}\sigma_i^r\sigma_j^{\hat{r}}\xi_1^T(t)\tilde{\Phi}^{1ij}\xi_1(t)\\ &= \sum_{i=1}^{w}\sum_{j=1}^{w}\sigma_i^r\sigma_j^{\hat{r}}\xi_1^T(t)\tilde{\Phi}^{1ij}\xi_1(t)\\ &\quad + \sum_{i=1}^{w}\sum_{j=1}^{w}\sigma_i^r\left(\sigma_j^r - \sigma_j^{\hat{r}}\right)\xi_1^T(t)\Xi_i\xi_1(t)\\ &= \sum_{i=1}^{w}\sum_{j=1}^{w}\sigma_i^r\sigma_j^{\hat{r}}\xi_1^T(t)\left(\tilde{\Phi}^{1ij} - \Xi_i\right)\xi_1(t)\\ &\quad + \sum_{i=1}^{w}\sum_{j=1}^{w}\sigma_i^r\sigma_j^r\xi_1^T(t)\Xi_i\xi_1(t).\end{aligned} \tag{28}$$

By using the Schur complement, one knows that (16) is equivalent to $\tilde{\Phi}^{1ij} - \Xi_i < 0$. Then, based on the assumption that $\sigma_j^{\hat{r}} \ge \kappa_j\sigma_j^r$, from (28), we have

$$\begin{aligned}&\sum_{i=1}^{w}\sum_{j=1}^{w}\sigma_i^r\sigma_j^{\hat{r}}\xi_1^T(t)\tilde{\Phi}^{1ij}\xi_1(t)\\ &\le \sum_{i=1}^{w}\sum_{j=1}^{w}\sigma_i^r\sigma_j^r\xi_1^T(t)\kappa_j\left(\tilde{\Phi}^{1ij} - \Xi_i\right)\xi_1(t)\\ &\quad + \sum_{i=1}^{w}\sum_{j=1}^{w}\sigma_i^r\sigma_j^r\xi_1^T(t)\Xi_i\xi_1(t)\\ &\le \sum_{i=1}^{w}\sigma_i^r\sigma_i^r\xi_1^T(t)\left[\kappa_i\left(\tilde{\Phi}^{1ii} - \Xi_i\right) + \Xi_i\right]\xi_1(t)\\ &\quad + \sum_{i=1}^{w}\sum_{i<j}\sigma_i^r\sigma_j^r\xi_1^T(t)\left[\kappa_j\left(\tilde{\Phi}^{1ij} - \Xi_i\right) + \kappa_i\left(\tilde{\Phi}^{1ji} - \Xi_j\right)\right.\\ &\qquad\qquad \left. +\ \Xi_i + \Xi_j\right]\xi_1(t).\end{aligned} \tag{29}$$

By utilizing the Schur complement to (17) together with (26) and (29), one can conclude that

$$\dot{V}_1(t) + 2\beta_1 V_1(t) + e_f^T(t)e_f(t) - \gamma^2\omega^T(t)\omega(t) \le 0. \tag{30}$$

Next, we consider the case of $m = 2$. Using a similar method, we can also obtain

$$\dot{V}_2(t) - 2\beta_2 V_2(t) + e_f^T(t)e_f(t) - \gamma^2\omega^T(t)\omega(t) \le 0. \tag{31}$$

For $\omega(t) = 0$, from (30) and (31), one has

$$V_m(t) \le \begin{cases} e^{-2\beta_1(t-T_{1,n})}V_1\left(T_{1,n}\right), & t \in \mathfrak{D}_{1,n} \\ e^{2\beta_2(t-T_{2,n})}V_2\left(T_{2,n}\right), & t \in \mathfrak{D}_{2,n}.\end{cases} \tag{32}$$

By combining the constraints of (18)–(22), one can obtain

$$V_m\big(T_{m,n}\big) \le \varrho_{3-m} V_{3-m}\big(T_{m,n}^-\big) \tag{33}$$

for $m = 1, 2$, respectively.

For $m = 1$, that is, $t \in \mathfrak{D}_{1,n}$, from (32) and (33), one can obtain

$$\begin{aligned} V(t) &\le \varrho_2 e^{-2\beta_1(t-T_{1,n})} V_2\Big(T_{1,n}^-\Big) \\ &\le \varrho_2 e^{2\beta_2 T_a^{n-1} - 2\beta_1(t-T_{1,n})} V_2\big(T_{2,n-1}\big) \\ &\le \varrho_0\varrho_2 e^{2(\beta_1+\beta_2)h + 2\beta_2 T_a^{n-1} - 2\beta_1(t-T_{1,n})} V_1\Big(T_{2,n-1}^-\Big). \end{aligned}$$

Then, one has

$$V(t) \le e^{-\upsilon(t)} V(0) \tag{34}$$

where $\upsilon(t) = 2[\beta_1 \sum_{i=0}^{n-1} T_s^i - \beta_2 \sum_{i=0}^{n-1} T_a^i - n(\beta_1+\beta_2)h - n\ln\sqrt{\varrho_0\varrho_2} + \beta_1(t - T_{1,n})]$ and T_a^n and T_s^n are defined in Section II.

Defining $\bar{\upsilon} = \beta_1 T_s^{\min} - \beta_2 T_a^{\max} - (\beta_1+\beta_2)h - \ln\sqrt{\varrho_0\varrho_2}$ leads to $n\bar{\upsilon} \le \upsilon(t)$. Then, it can be concluded that

$$V(t) < e^{-2n\bar{\upsilon}} V(0) \tag{35}$$

which implies that $t \le (n+1)T - T_a$.

Therefore, it is true that

$$-n\bar{\upsilon} \le -\frac{\bar{\upsilon}}{T}t + \frac{(T-T_a)\bar{\upsilon}}{T}. \tag{36}$$

Then, we have

$$V(t) \le V_1(0) e^{\frac{2\bar{\upsilon}(T-T_a)}{T}} e^{-\frac{2\bar{\upsilon}}{T}t}. \tag{37}$$

Furthermore, from (35), one can determine that the maximum of DoS duration in Theorem 1 should be held to guarantee that the system has a certain decay rate.

For $m = 2$, that is, $t \in \mathfrak{D}_{2,n}$, using a similar method, one can obtain

$$V(t) \le \frac{1}{\varrho_2} V_1(0) e^{-\frac{2\bar{\upsilon}}{T}t}. \tag{38}$$

Defining $\Lambda = \max\{(1/\varrho_2), e^{([\bar{\upsilon}(T-T_a)]/T)}\}$ and combining (37) and (38) yield that

$$V(t) \le \Lambda V_1(0) e^{-\frac{2\bar{\upsilon}}{T}t}, \quad t \ge 0. \tag{39}$$

By recalling (22), it follows that:

$$V(t) \ge \frac{1}{a}\|x(t)\|^2,\ V_1(0) \le b\|\xi_1(0)\|_h^2 \tag{40}$$

where $a = \min^{-1}\{\lambda_{\min}(P_m)\}$ and $b = \max\{\lambda_{\max}(P_m) + h\lambda_{\max}(Q_m) + (h^2/2)\lambda_{\max}(L_m)\}$.

By combining (39) and (40), one obtains

$$\|x(t)\| \le \vartheta e^{-\frac{\bar{\upsilon}}{T}t} \tag{41}$$

where $\vartheta = \sqrt{ab\Lambda}\|\xi_1(0)\|_h$. Then, we can conclude that system (15) is exponentially stable with the decay rate $(\bar{\upsilon}/T)$.

For $\omega(t) \ne 0$, integrating (30) and (31) from $T_{1,n}$ to t, it follows that:

$$\sum_{i=0}^{n} \int_{T_{1,n}}^{t} \Big[\dot{V}_m(t) - (-1)^m 2\beta_m V_m(t) + e_f^T(t)e_f(t) - \gamma^2\omega^T(t)\omega(t)\Big]dt \le 0. \tag{42}$$

Since $V_m(t) > 0$, from (32), one can determine that $\sum_{i=0}^{n}\int_{T_{1,n}}^{t}[e_f^T(t)e_f(t) - \gamma^2\omega^T(t)\omega(t)]dt < 0$ under $V(0) = 0$. Let $n \to 0$; then, we have

$$\int_0^\infty \|e_f(t)\|^2 dt \le \gamma^2 \int_0^\infty \|\omega(t)\|^2 dt. \tag{43}$$

This ends the proof. ■

Sufficient conditions that ensure the exponential stability of the system (15) subject to DoS attacks are derived in Theorem 1. Based on Theorem 1, a method of designing the filter and the ETM will be given in the following.

Theorem 2: For given prescribed scalars κ_i, β_1, β_2, $\varrho_0, \varrho_2, \rho, \ell_1, \ell_2$, and γ, by using the ETM in (10), the filtering error system (15) considering DoS attacks with the maximum DoS duration time $T_a^{\max} = ([\beta_1 T - \ln\sqrt{\varrho_0\varrho_2}]/[(\beta_1+\beta_2)]) - h$ into account is exponentially stable, if there exist matrices $P_{m1} > 0, P_{m3} > 0, \Omega_p > 0, Q_m > 0, Y_m > 0, V_m > 0, L_{mp} > 0$, $U_{mp} > 0$ and $P_{m2}, W_m, \hat{A}_{fmj}, \hat{B}_{fpj}, \hat{C}_{fmj}$ with appropriate dimensions such that

$$\bar{\Phi}^{mij} < 0 \tag{44}$$

$$\kappa_i\bar{\Phi}^{mij} + \kappa_j\bar{\Phi}^{mji} + \tilde{\Xi}_i + \tilde{\Xi}_j < 0, \quad (i \le j) \tag{45}$$

$$P_{m1} - Y_m > 0 \tag{46}$$

$$\begin{bmatrix} P_{(3-m)1} - \varrho_m P_{m1} & * \\ W_m - \varrho_m Y_m & V_m - \varrho_m Y_m \end{bmatrix} \le 0 \tag{47}$$

$$Q_m \le \varrho_{4-2m} Q_{3-m} \tag{48}$$

$$L_{mp} \le \varrho_{4-2m} L_{(3-m)p} \tag{49}$$

$$\begin{bmatrix} L_{mp} & * \\ U_{mp}^T & L_{mp} \end{bmatrix} \ge 0 \tag{50}$$

with $m = 1, 2;\ i, j \in \mathscr{I}, p \in \mathcal{V}$, where

$$\bar{\Phi}^{mij} = \begin{bmatrix} \hat{\Phi}_{11}^{mij} - \tilde{\Xi}_i & * \\ \hat{\Phi}_{21}^{mij} & \hat{\Phi}_{22}^{m} \end{bmatrix}$$

$$\hat{\Phi}_{11}^{1ij} = \begin{bmatrix} \hat{\Psi}_{11i}^1 & * & * & * & * & * \\ \hat{\Psi}_{ij}^1 & \hat{\Psi}_{Yj}^1 & * & * & * & * \\ \hat{\Psi}_{21}^1 & 0 & \Psi_{22}^1 & * & * & * \\ \overline{B}_i^T P_{11} & \overline{B}_i^T Y_1 & 0 & -\gamma^2 I & * & * \\ \hat{\Psi}_{41ij}^1 & \hat{\Psi}_{Bij}^1 & \Psi_{42}^1 & 0 & \Psi_{44i}^1 & * \\ \hat{\Psi}_{51j}^1 & \hat{\Psi}_{52j}^1 & 0 & 0 & \Psi_{54i}^1 & \Psi_{55}^1 \end{bmatrix}$$

$$\hat{\Phi}_{11}^{2ij} = \begin{bmatrix} \hat{\Psi}_{11i}^2 & * & * & * & * \\ \hat{\Psi}_{ij}^2 & \hat{\Psi}_{Yj}^2 & * & * & * \\ \hat{\Psi}_{21}^2 & 0 & \Psi_{22}^2 & * & * \\ \overline{B}_i^T P_{21} & \overline{B}_i^T Y_2 & 0 & -\gamma^2 I & * \\ \hat{\Psi}_{41ij}^2 & 0 & \Psi_{42}^2 & 0 & \Psi_{44i}^2 \end{bmatrix}$$

$$\hat{\Psi}_{11i}^m = Q_m + \mathrm{Sym}\Big\{(-1)^{m+1}\beta_m P_{m1} + P_{m1}\overline{A}_i\Big\} - \frac{\varpi_m}{h}\sum_{p=1}^{N} L_{mp}$$

$$\hat{\Psi}_{ij}^m = Y_m\overline{A}_i + \hat{A}_{fmj}^T + \mathrm{Sym}\Big\{(-1)^{m+1}\beta_m Y_m\Big\}$$

$$\hat{\Psi}_{21}^m = \frac{\varpi_m}{h}\sum_{p=1}^{N} U_{mp}^T,\ \hat{\Psi}_{41ij}^m = \mathrm{col}_N\Big\{\hat{\mathcal{L}}_{mp}^4\Big\}$$

$$\hat{\mathcal{L}}_{mp}^4 = (2-m)\lambda_p\left\{\hat{B}_{fpj}(\mathcal{W}\otimes I)\hat{C}_i\right\}^T + \frac{\varpi_m}{h}\left(L^T{}_{mp} - U_{mp}^T\right)$$
$$\hat{\Psi}_{51j}^1 = \hat{\Psi}_{52j}^1 = \mathrm{col}_N\left\{\frac{\lambda_p}{\mu}\hat{B}_{fpj}^T\right\}$$
$$\hat{\Psi}_{Yj}^m = \mathrm{Sym}\left\{(-1)^{m+1}\beta_m Y_m + \hat{A}_{fmj}\right\}$$
$$\hat{\Psi}_{Bij}^1 = \mathrm{col}_N\left\{\lambda_p\left\{\hat{B}_{fpj}(\mathcal{W}\otimes I)\hat{C}_i\right\}^T\right\}$$
$$\hat{\Phi}_{21}^{mij} = \begin{bmatrix}\hat{\Phi}_{1m}^{i^T} & \hat{\Phi}_{2m}^{ij^T}\end{bmatrix}^T, \hat{\Phi}_{22}^m = \mathrm{diag}\left\{-2k_m I + k_m^2 L_{mp}, -I\right\}$$
$$\hat{\Phi}_{11}^i = \sqrt{h}\begin{bmatrix}\mathrm{col}_N\{\overline{A}_i\} & 0 & 0 & \mathrm{col}_N\{\overline{B}_i\} & 0 & 0\end{bmatrix}$$
$$\hat{\Phi}_{12}^i = \sqrt{h}\begin{bmatrix}\mathrm{col}_N\{\overline{A}_i\} & 0 & 0 & \mathrm{col}_N\{\overline{B}_i\} & 0\end{bmatrix}$$
$$\hat{\Phi}_{21}^{ij} = \frac{1}{N}\begin{bmatrix}\overline{E}_i & -\hat{C}_{fmj} & 0 & 0 & 0 & 0\end{bmatrix}$$
$$\hat{\Phi}_{22}^{ij} = \frac{1}{N}\begin{bmatrix}\overline{E}_i & -\hat{C}_{fmj} & 0 & 0 & 0\end{bmatrix}$$

and other symbols are defined in Theorem 1. Moreover, the filter parameters are designed as

$$\begin{cases}\overline{A}_{fmj} = P_{m2}^{-1}\hat{A}_{fmj}P_{m2}^{-T}P_{m3}\\ \overline{B}_{fpj} = P_{12}^{-1}\hat{B}_{fpj}\\ \overline{C}_{fmj} = \hat{C}_{fmj}P_{m2}^{T}P_{m3}.\end{cases} \tag{51}$$

Proof: Define $P_m = \begin{bmatrix}P_{m1} & P_{m2}\\ * & P_{m3}\end{bmatrix} > 0$, and matrix $Y_m = P_{m2}P_{m3}^{-1}P_{m2}^T$. Using the Schur complement to P_m leads to (46).

From (18) with $m = 2$, it follows that:

$$\begin{bmatrix}P_{11} - \varrho_2 P_{21} & *\\ P_{12}^T - \varrho_2 P_{22}^T & P_{13} - \varrho_2 P_{23}\end{bmatrix} \le 0. \tag{52}$$

Define $W_2 = P_{22}P_{23}^{-1}P_{12}^T$ and $V_2 = P_{22}P_{23}^{-1}P_{13}P_{23}^{-1}P_{22}^T$. By premultiplying and postmultiplying (52) with $P_{22}P_{23}^{-1}$ and its transpose, one can easily determine that (47) with $m = 2$ holds. Similarly, we can deduce that (47) with $m = 1$ is equivalent to $P_2 \le \varrho_1 P_1$.

For $L_{mp} > 0$ and $k_m > 0$, we know that

$$\left(L_{mp} - k_m^{-1}I\right)L_{mp}^{-1}\left(L_{mp} - k_m^{-1}I\right) \ge 0. \tag{53}$$

It follows that:

$$-L_{mp}^{-1} \le -2k_m I + k_m^2 L_{mp}. \tag{54}$$

Define $\Pi_m = \begin{bmatrix}I & 0\\ 0 & P_{m2}P_{m3}^{-1}\end{bmatrix}$, and premultiply and postmultiply (16) and (17) with $\mathrm{diag}\{\Pi_m, I, I, I, I, I\}$ and its transpose. We can conclude that (44) and (45) hold with $\hat{A}_{fmj} = P_{m2}\overline{A}_{fmj}P_{m3}^{-1}P_{m2}^T$, $\hat{B}_{fpj} = P_{12}\overline{B}_{fpj}$, and $\hat{C}_{fmj} = \overline{C}_{fmj}P_{m3}^{-1}P_{m2}^T$. Similar to the method of [20], the filter parameters in (51) can be obtained. This completes the proof. ■

Remark 6: Multisensors are utilized in this study to obtain the precision, low cost, and reliability of the filter, which inevitably leads to computational complexity. Therefore, this method is suitable for using precise estimation without many sensors, although the parameters of the filter are calculated offline.

IV. Simulation Example

To verify the effectiveness of the proposed method, we consider the nonlinear fuzzy system (3) with the parameters below [38] to investigate the estimation performance of the system with multisensors against DoS attacks

$$A_1 = \begin{bmatrix}-3 & 1 & 0\\ 0.3 & -2.5 & 1\\ -0.1 & 0.3 & -3.8\end{bmatrix}, B_1 = \begin{bmatrix}1\\0\\1\end{bmatrix}$$
$$A_2 = \begin{bmatrix}-2.5 & 0.5 & -0.1\\ 0.1 & -3.5 & 0.3\\ -0.1 & 1 & -2\end{bmatrix}, B_2 = \begin{bmatrix}-0.6\\0.5\\0\end{bmatrix}$$
$$E_1 = \begin{bmatrix}0.8 & 0.3 & 0\end{bmatrix}, E_2 = \begin{bmatrix}-0.5 & 0.2 & 0.3\end{bmatrix}$$
$$C_{1i} = \begin{bmatrix}0.1 & 0 & 0.1\end{bmatrix}, C_{2i} = \begin{bmatrix}0.2 & 0.1 & 0.2\end{bmatrix}$$
$$C_{3i} = \begin{bmatrix}0.5 & 0.7 & 0.2\end{bmatrix}, C_{4i} = \begin{bmatrix}0.4 & 0.7 & 0.2\end{bmatrix}$$

with $i = 1, 2$. The membership function of the fuzzy system is defined as

$$\sigma_1(t) = \frac{1}{1 + e^{-3x_1(t)}}, \sigma_2(t) = 1 - \sigma_1(t).$$

There are four sensor nodes with the weighted adjacency matrix $\mathcal{W}_1$

$$\mathcal{W}_1 = \begin{bmatrix}0.5 & 0.3 & 0.1 & 0.1\\ 0.3 & 0.5 & 0.1 & 0.1\\ 0.1 & 0.1 & 0.5 & 0.3\\ 0.1 & 0.1 & 0.3 & 0.5\end{bmatrix}, \mathcal{W}_2 = \begin{bmatrix}0 & 0.3 & 0.1 & 0\\ 0 & 0.5 & 0 & 0.1\\ 0 & 0 & 0 & 0\\ 0 & 0.1 & 0 & 0.5\end{bmatrix}.$$

Set the initial state as $x(0) = \begin{bmatrix}-0.3 & 0.1 & -0.3\end{bmatrix}^T$. To study the impact of the proposed ETM on the amount of data releasing for the system with disturbance, we set the disturbance as

$$\omega(t) = \begin{cases}0, & t < 4 \text{ s}\\ 0.6e^{-5(t-4)}\sin 10(t-4), & t \ge 4 \text{ s}.\end{cases}$$

The chosen adjustment factor (7) is $\mu = 0.3$. The sampling period is $h = 0.01$ s. Choose $\kappa_1 = 0.9$, $\kappa_2 = 0.75$, $\varrho_0 = \varrho_2 = 1.01$, $\ell_1 = 0.006$, $\ell_2 = 0.01$, $\beta_1 = 0.2$, and $\beta_2 = 0.06$. By applying Theorem 2 with the H_∞ performance level $\gamma = 2$, one can obtain the filter parameters and the weight matrix of the ETM by the LMI toolbox, which are omitted here due to space limitation.

Figs. 3 and 4 show the simulation results using the proposed ETM and the structure of the filter in Fig. 1 with the obtained parameters. In Fig. 3, the dashed-dotted red line denotes the estimated filter output and the blue line represents the estimated system output. From Figs. 3 and 4, one can conclude that the filter can effectively estimate the system output under DoS attacks (the DoS active periods are the yellow area shown in Fig. 5) and channel fading with $\lambda_p = 0.9$ by using the proposed ETM and the resilient filter design method. Fig. 5 shows the effective releasing instants and their intervals with this method. $\bar{l}$ represents the number of sampling packets being discarded. The network bandwidth burden is significantly relieved due to the substantial reduction of the number of releasing packets, which further demonstrates the results in Table I.

Table I shows that with the proposed method the average releasing rate (ARR) during 4–5 s is much more than the one

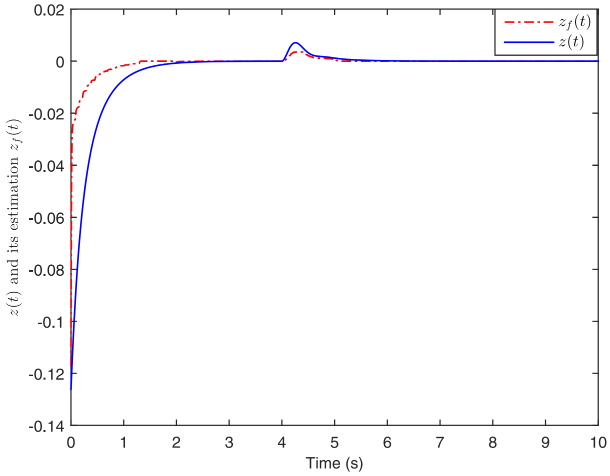


Fig. 3. Responses of $z(t)$ and estimation $z_f(t)$.

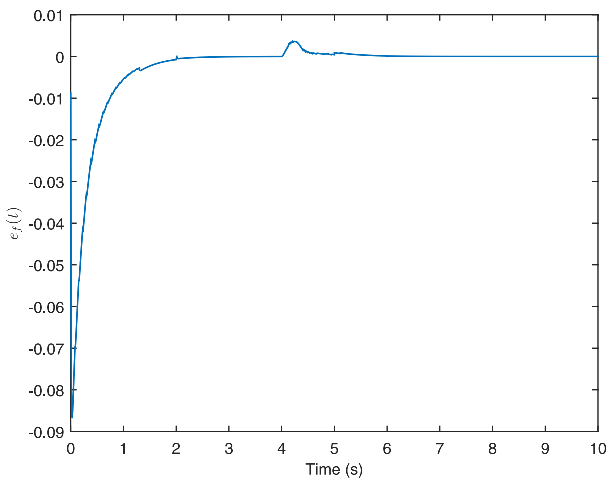


Fig. 4. Filtering error.

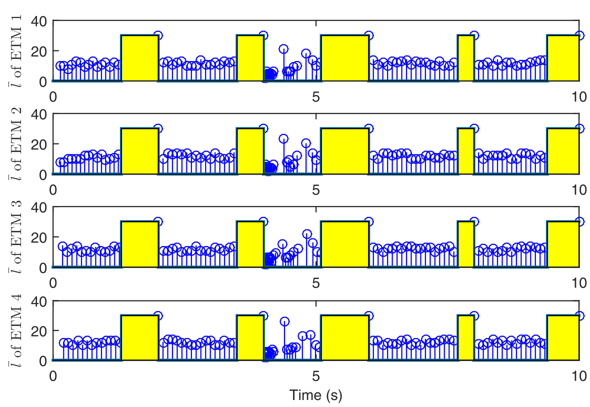


Fig. 5. Effective releasing instants and their responding $\bar{l}$ with the proposed ETM.

during other periods. This implies that the proposed ETM is sensitive to the disturbance. Much more data are sent to the filter when the system has external disturbance, which results in a better estimation performance.

If one sets $\mu = 1$ and $\ell_2 = 0$, the ETM in (9) reduces to the traditional one, for which one can depict the effective releasing instants in Fig. 6. It is clear that the proposed

TABLE I
ARR OF THE iTH ETM$(i = 1, 2, 3, 4)$

	$t \in [0, 10)$	$t \in [4, 5)$
ARR of ETM 1	8.6%	18.6%
ARR of ETM 2	9.8%	20.4%
ARR of ETM 3	8.4%	18.2%
ARR of ETM 4	8.8%	18.9%

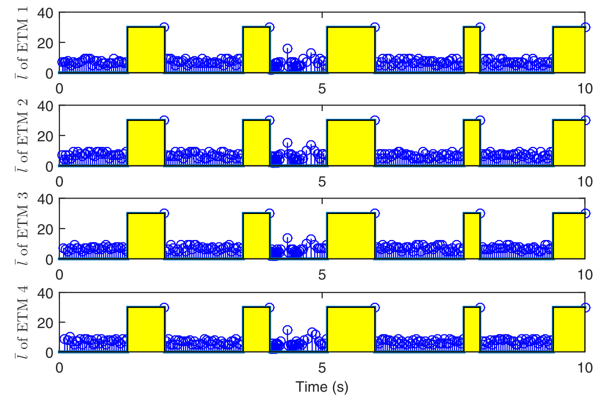


Fig. 6. Effective release instants and their responding $\bar{l}$ with the traditional ETM.

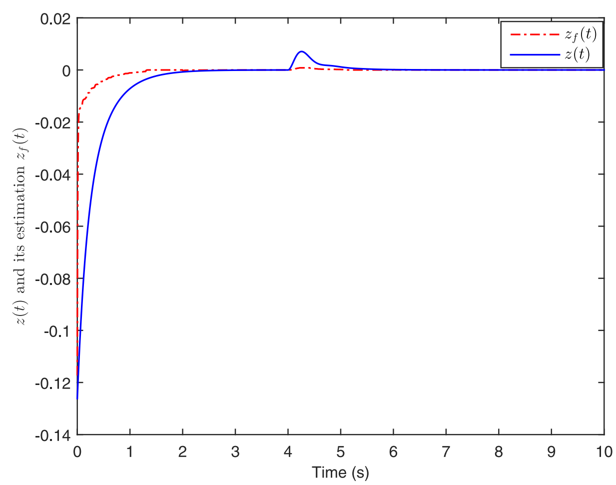


Fig. 7. Responses of $z(t)$ and estimation $z_f(t)$ with $\mathcal{W}_2$.

method can save much more communication resources than the traditional one under the same triggering threshold ℓ_1 by comparing Figs. 5 and 6.

As stated in Remark 1, the structure of multisensors can enhance the reliability of filtering systems. Next, we assume that the weighted adjacency matrix changes to $\mathcal{W}_2$, from which one can see that the communication of nodes 1 and 3 has failed. As shown in Fig. 7, one can also obtain an expected result by using the weighted fusion method.

V. Conclusion

In this article, the problem of networked fuzzy H_∞ filter design has been studied for nonlinear systems against DoS attacks. Preliminary data fusion was considered for multisensors before releasing packets into the network. To address the problem of reducing the network burden, a new ETM was proposed, through which the ARR could be greatly decreased, while the amount of data releasing when the system had external disturbance was much higher than in similar time intervals. A switched filtering error model considering both the ETM and DoS attacks was established. Based on the switched model, sufficient conditions were derived to obtain resilient filtering results by applying the piecewise Lyapunov–Krasovskii method. Finally, a numerical example was utilized to demonstrate the effectiveness of the proposed method.

REFERENCES

[1] E. Tian and D. Yue, "Reliable H_∞ filter design for T–S fuzzy model-based networked control systems with random sensor failure," *Int. J. Robust Nonlinear Control*, vol. 23, no. 1, pp. 15–32, Sep. 2013.

[2] S. Zhang, D. Ding, G. Wei, J. Mao, Y. Liu, and F. E. Alsaadi, "Design and analysis of H_∞ filter for a class of T–S fuzzy system with redundant channels and multiplicative noises," *Neurocomputing*, vol. 260, pp. 257–264, Oct. 2017.

[3] H. D. Choi, C. K. Ahn, P. Shi, L. Wu, and M. T. Lim, "Dynamic output-feedback dissipative control for T–S fuzzy systems with time-varying input delay and output constraints," *IEEE Trans. Fuzzy Syst.*, vol. 25, no. 3, pp. 511–526, Jun. 2017.

[4] J. Liu, W. Suo, L. Zha, E. Tian, and X. Xie, "Security distributed state estimation for nonlinear networked systems against DoS attacks," *Int. J. Robust Nonlin. Control*, vol, 30, no. 3, pp. 1156–1180, Dec. 2020.

[5] S. Li, C. K. Ahn, and Z. Xiang, "Sampled-data adaptive output feedback fuzzy stabilization for switched nonlinear systems with asynchronous switching" *IEEE Trans. Fuzzy Syst.*, vol. 27, no. 1, pp. 200–205, Jan. 2019.

[6] F. Yang, Q.-L. Han, and Y. Liu, "Distributed H_∞ state estimation over a filtering network with time-varying and switching topology and partial information exchange," *IEEE Trans. Cybern.*, vol. 49, no. 3, pp. 870–882, Mar. 2019.

[7] C. Wen, Z. Wang, Q. Liu, and F. E. Alsaadi, "Recursive distributed filtering for a class of state-saturated systems with fading measurements and quantization effects," *IEEE Trans. Syst., Man, Cybern., Syst.*, vol. 48, no. 6, pp. 930–941, Jun. 2018.

[8] Y. Zhao, X. He, and D. Zhou, "Distributed filtering for time-varying networked systems with sensor gain degradation and energy constraint: A centralized finite-time communication protocol scheme," *China Inf. Sci.*, vol. 61, no. 9, Aug. 2018, Art. no. 092208.

[9] X. Ge, Q.-L. Han, X.-M. Zhang, L. Ding, and F. Yang, "Distributed event-triggered estimation over sensor networks: A survey," *IEEE Trans. Cybern.*, vol. 50, no. 3, pp. 1306–1320, Mar. 2020.

[10] X.-M. Zhang and Q.-L. Han, "Event-triggered H_∞ control for a class of nonlinear networked control systems using novel integral inequalities," *Int. J. Robust Nonlin. Control*, vol. 27, no. 4, pp. 679–700, Apr. 2017.

[11] S. Sui, C. L. P. Chen, and S. Tong, "Event-trigger-based finite-time fuzzy adaptive control for stochastic nonlinear system with unmodeled dynamics," *IEEE Trans. Fuzzy Syst.*, early access, Apr. 20, 2020, doi: 10.1109/TFUZZ.2020.2988849.

[12] B.-L. Zhang, Q.-L. Han, and X.-M. Zhang, "Recent advances in vibration control of offshore platforms," *Nonlinear Dyn.*, vol. 89, no. 2, pp. 755–771, 2017.

[13] X. Wang and M. D. Lemmon, "Self-triggered feedback control systems with finite-gain L_2 stability," *IEEE Trans. Autom. Control*, vol. 54, no. 3, pp. 452–467, Mar. 2009.

[14] W. P. M. H. Heemels, A. R. Teel, and M. C. F. Donkers, "Periodic event-triggered control for linear systems," *IEEE Trans. Autom. Control*, vol. 58, no. 4, pp. 847–861, Apr. 2013.

[15] D. Yue, E. Tian, and Q.-L. Han, "A delay system method for designing event-triggered controllers of networked control systems," *IEEE Trans. Autom. Control*, vol. 58, no. 2, pp. 475–481, Feb. 2013.

[16] X. Li, X. Dong, Q. Li, and R. Zhang, "Event-triggered time-varying formation control for general linear multi-agent systems," *J. Franklin Inst.*, vol. 356, no. 17, pp. 10179–10195, Nov. 2019.

[17] Z.-G. Wu, Y. Xu, Y.-J. Pan, H. Su, and Y. Tang, "Event-triggered control for consensus problem in multi-agent systems with quantized relative state measurements and external disturbance," *IEEE Trans. Circuits Syst. I, Reg. Papers*, vol. 65, no. 7, pp. 2232–2242, Jul. 2018.

[18] B.-L. Zhang, Q.-L. Han, and X.-M. Zhang, "Event-triggered H_∞ reliable control for offshore structures in network environments," *J. Sound Vib.*, vol. 368, pp. 1–21, Apr. 2016.

[19] Y. Wang, Y. Xia, C. K. Ahn, and Y. Zhu, "Exponential stabilization of Takagi-Sugeno fuzzy systems with aperiodic sampling: An aperiodic adaptive event-triggered method," *IEEE Trans. Syst., Man, Cybern.: Syst.*, vol. 49, no. 2, pp. 444–454, Feb. 2019.

[20] Z. Gu, P. Shi, D. Yue, and Z. Ding, "Decentralized adaptive event-triggered H_∞ filtering for a class of networked nonlinear interconnected systems," *IEEE Trans. Cybern.*, vol. 49, no. 5, pp. 1570–1579, May 2019.

[21] Z. Zhang, H. Liang, C. Wu, and C. K. Ahn, "Adaptive event-triggered output feedback fuzzy control for nonlinear networked systems with packet dropouts and actuator failure," *IEEE Trans. Fuzzy Syst.*, vol. 27, no. 9, pp. 1793–1806, Sep. 2019.

[22] L. Wang and C. L. P. Chen, "Reduced-order observer-based dynamic event-triggered adaptive NN control for stochastic nonlinear systems subject to unknown input saturation," *IEEE Trans. Neural Netw. Learn. Syst.*, early access, May 19, 2020, doi: 10.1109/TNNLS.2020.2986281.

[23] X. Ge, Q.-L. Han, M. Zhong, and X.-M. Zhang, "Distributed Krein space-based attack detection over sensor networks under deception attacks," *Automatica*, vol. 109, Nov. 2019, Art. no. 108557.

[24] J. Liu, J. Xia, E. Tian, and S. Fei, "Hybrid-driven-based H_∞ filter design for neural networks subject to deception attacks," *Appl. Math. Comput.*, vol. 320, pp. 158–174, Mar. 2018.

[25] D. Ding, Z. Wang, D. W. Ho, and G. Wei, "Observer-based event-triggering consensus control for multiagent systems with lossy sensors and cyber-attacks," *IEEE Trans. Cybern.*, vol. 47, no. 8, pp. 1936–1947, Aug. 2017.

[26] D. Zhang, L. Liu, and G. Feng, "Consensus of heterogeneous linear multiagent systems subject to aperiodic sampled-data and DoS attack," *IEEE Trans. Cybern.*, vol. 49, no. 4, pp. 1501–1511, Apr. 2019.

[27] X.-M. Zhang, Q.-L. Han, X. Ge, and L. Ding, "Resilient control design based on a sampled-data model for a class of networked control systems under denial-of-service attacks," *IEEE Trans. Cybern.*, vol. 50, no. 8, pp. 3616–3626, Aug. 2020.

[28] S. Hu, D. Yue, Q.-L. Han, X. Xie, X. Chen, and C. Dou, "Observer-based event-triggered control for networked linear systems subject to denial-of-service attacks," *IEEE Trans. Cybern.*, vol. 49, no. 5, pp. 1952–1964, May 2020.

[29] Z. Gu, P. Shi, D. Yue, S. Yan and X. Xie, "Memory-based continuous event-triggered control for networked T-S fuzzy systems against cyber-attacks," *IEEE Trans. Fuzzy Syst.*, early access, Jul. 29, 2020, doi: 10.1109/TFUZZ.2020.3012771.

[30] S. Li, C. K. Ahn, and Z. Xiang, "Command filter based adaptive fuzzy finite-time control for switched nonlinear systems using state-dependent switching method," *IEEE Trans. Fuzzy Syst.*, early access, Jan. 13, 2020, doi: 10.1109/TFUZZ.2020.2965917.

[31] O. Kwon, M.-J. Park, J. H. Park, and S.-M. Lee, "Stability and stabilization of T-S fuzzy systems with time-varying delays via augmented Lyapunov-Krasovskii functionals," *Inf. Sci.*, vol. 372, pp. 1–15, Dec. 2016.

[32] D. Liu and G.-H. Yang, "Decentralized event-triggered output feedback control for a class of interconnected large-scale systems," *ISA Trans.*, vol. 93, pp. 156–164, Oct. 2019.

[33] Z. Gu, X. Zhou, T. Zhang, F. Yang, and M. Shen, "Event-triggered filter design for nonlinear cyber-physical systems subject to deception attacks," *ISA Trans.*, vol. 104, pp. 130–137, Sep. 2020.

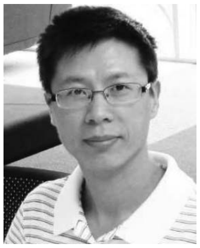
[34] Z. Li, H. Shu, and X. Kan, "H_∞ fault detection with randomly occurring nonlinearities and channel fadings," *Int. J. Syst. Sci*, vol. 45, no. 7, pp. 1416–1426, Oct. 2014.

[35] H. Yan, H. Zhang, F. Yang, X. Zhan, and C. Peng, "Event-triggered asynchronous guaranteed cost control for Markov jump discrete-time neural networks with distributed delay and channel fading," *IEEE Trans. Neural Netw. Learn. Syst.*, vol. 29, no. 8, pp. 3588–3598, Aug. 2018.

[36] E. Tian and C. Peng, "Memory-based event-triggering H∞ load frequency control for power systems under deception attacks," *IEEE Trans. Cybern.*, early access, Mar. 12, 2020, doi: 10.1109/TCYB.2020.2972384.

[37] R. Lu, S. Liu, H. Peng, Y. Xu, and K. Xie, "Non-fragile filtering for fuzzy stochastic systems over fading channel," *Neurocomputing*, vol. 174, pp. 553–559, Jan. 2016.

[38] H. Wang, P. Shi, and J. Zhang, "Event-triggered fuzzy filtering for a class of nonlinear networked control systems," *Signal Process.*, vol. 113, pp. 159–168, Aug. 2015.



Zhou Gu (Member, IEEE) received the B.S. degree in automation from North China Electric Power University, Beijing, China, in 1997, and the M.S. and Ph.D. degrees in control science and engineering from the Nanjing University of Aeronautics and Astronautics, Nanjing, China, in 2007 and 2010, respectively.

From 1999 to 2013, he was with the School of Power Engineering, Nanjing Normal University, Nanjing, as an Associate Professor. He is currently a Professor with Nanjing Forestry University, Nanjing. His current research interests include networked control systems, time-delay systems, and reliable control and their applications.

Choon Ki Ahn (Senior Member, IEEE) received the B.S. and M.S. degrees in electrical engineering from Korea University, Seoul, South Korea, in 2000 and 2002, respectively, and the Ph.D. degree in electrical engineering and computer science from Seoul National University, Seoul, in 2006.

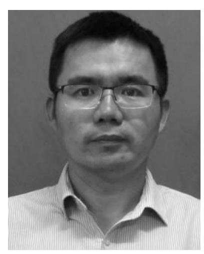
He is currently a *Crimson Professor of Excellence* with the College of Engineering and a Full Professor with the School of Electrical Engineering, Korea University. His current research interests are control, estimation, fuzzy systems, neural networks, and nonlinear dynamics.

Prof. Ahn was a recipient of the Early Career Research Award and the Excellent Research Achievement Award of Korea University in 2015 and 2016, respectively. He was awarded the Medal for "Top 100 Engineers" 2010 by IBC, Cambridge, U.K. In 2016, he was ranked #1 in Electrical/Electronic Engineering and #2 in entire areas of Engineering among Korean young professors based on paper quality. He received the Presidential Young Scientist Award from the President of South Korea in 2017, and the Research Excellence Award from Korea University (Top 3% Professor of Korea University in Research) in 2019 and 2020. He was a recipient of the Highly Cited Researcher Award in Engineering by Clarivate Analytics (formerly, Thomson Reuters). He has been on the Editorial Board of leading international journals, including the *IEEE Systems, Man, and Cybernetics Magazine*, IEEE TRANSACTIONS ON NEURAL NETWORKS AND LEARNING SYSTEMS, IEEE TRANSACTIONS ON FUZZY SYSTEMS, IEEE TRANSACTIONS ON SYSTEMS, MAN, AND CYBERNETICS: SYSTEMS, IEEE TRANSACTIONS ON AUTOMATION SCIENCE AND ENGINEERING, IEEE SYSTEMS JOURNAL, *Nonlinear Dynamics*, *Aerospace Science and Technology*, *Artificial Intelligence Review*, and other top-tier journals. He is a member of the IEEE Technical Committee on Cyber-Physical Systems; IEEE SMCS Technical Committee on Intelligent Learning in Control Systems; and IEEE SMCS Technical Committee on Soft Computing.

Dong Yue (Senior Member, IEEE) received the Ph.D. degree from the South China University of Technology, Guangzhou, China, in 1995.

He is currently a Changjiang Professor and the Dean of the Institute of Advanced Technology, Nanjing University of Posts and Telecommunications, Nanjing, China. His research interests include analysis and synthesis of networked control systems, multiagent systems, optimal control of power systems, and the Internet of Things.

Dr. Yue is currently an Associate Editor of the IEEE TRANSACTIONS ON INDUSTRIAL INFORMATICS, the IEEE TRANSACTIONS ON NEURAL NETWORKS AND LEARNING SYSTEMS, *Journal of the Franklin Institute*, *International Journal of Systems Science*, and the IEEE Control Systems Society Conference Editorial Board.



Xiangpeng Xie (Member, IEEE) received the B.S. and Ph.D. degrees in engineering from Northeastern University, Shenyang, China, in 2004 and 2010, respectively.

From 2012 to 2014, he was a Postdoctoral Fellow with the Department of Control Science and Engineering, Huazhong University of Science and Technology, Wuhan, China. He is currently a Professor with the Institute of Advanced Technology, Nanjing University of Posts and Telecommunications, Nanjing, China. His research interests include fuzzy modeling and control synthesis, state estimations, optimization in process industries, and intelligent optimization algorithms.